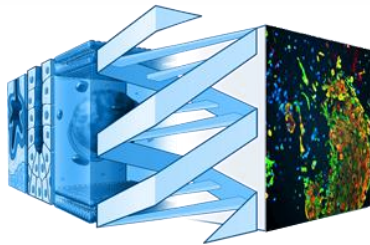




KNIGHT
CANCER INSTITUTE
Oregon Health & Science University



OHSU CENTER FOR SPATIAL
SYSTEMS BIOMEDICINE

Joe W. Gray, PhD
Gordon Moore Endowed Chair
Biomedical Engineering Department
Center for Spatial Systems Biomedicine
Knight Cancer Institute

Predicting responses to cancer therapies

Omics and beyond

KAVLI INSTITUTE FOR THEORETICAL PHYSICS
May 24, 2012

Omics and beyond

Topics for discussion

Today

- The state of the cancer “ome”
- Developing a molecular basis for therapeutic response
- Beyond genomics – understanding the micro- and nanoenvironments

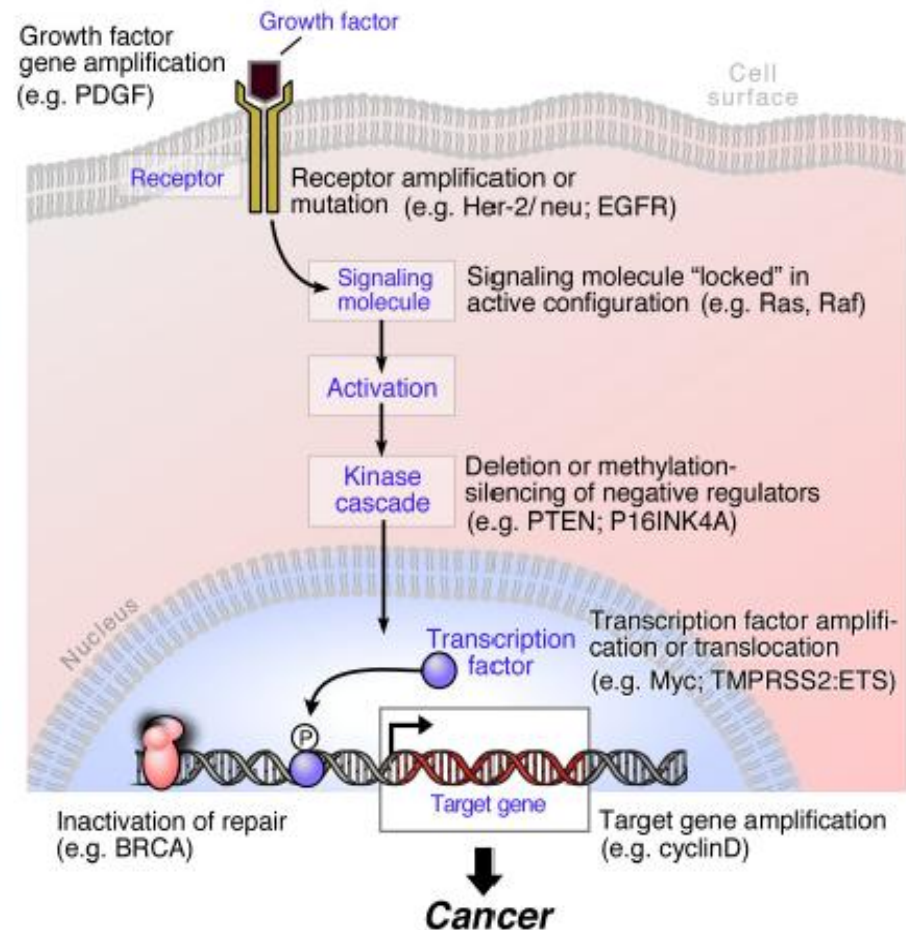
Tomorrow

Omics and beyond

Topics for discussion

- **The state of the cancer “ome”**
- Developing a molecular basis for therapeutic response
- Beyond genomics – understanding the micro- and nanoenvironments

Goals in cancer research



- Normal cells have established regulatory systems to control behavior (grow, die, move, secrete a protein, etc.)
- Cancers arise because of genetic damage
- Our goal in cancer treatment is to find the abnormalities and develop therapies to correct the defect

Investments in genome science have stimulated development of a wealth of “reductionist” tools to catalog omic components

Massively parallel DNA



Microarrays



Microfluidics and PCR

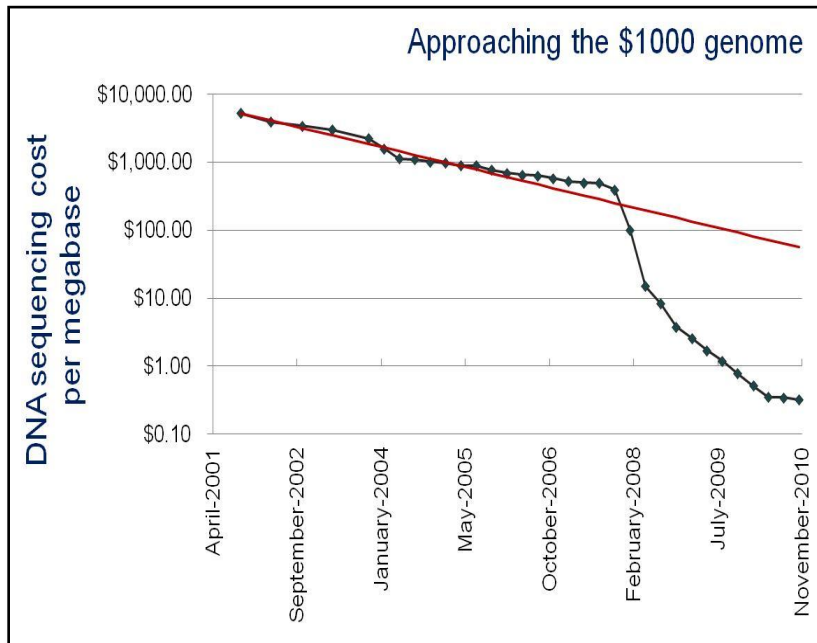


LC/mass spec



Plummeting costs and technological advances make ⁶ clinical applications increasingly practical

Nucleic acid sequencing



- Microgram to nanogram quantities of nucleic acids for copy number, mutation and promoter methylation
- Formalin fixed paraffin embedded capability
- Genome wide analysis ~\$1500/sample
- Real time (~1 hour), point of care diagnostics

International cancer genomics efforts are cataloging important genome aberrations in major tumor types

Recurrent aberrations will be defined for major tumor types in 3 -5 years



International Cancer Genome Consortium

ICGC Goal: To obtain a comprehensive description of genomic, transcriptomic and epigenomic changes in 50 different tumor types and/or subtypes which are of clinical and societal importance across the globe.

International network of cancer genome projects. Nature 464, 993-998 (15 April 2010)

ICGC Public Presentation April 15, 2010 : PDF | PPT

International Cancer Genome Consortium (ICGC) Goals, Structure, Policies and Guidelines : HTML | PDF

Members of the ICGC Committed Projects to date: 21

Brain Cancer United States	Lung Cancer United States
Breast Cancer European Union / United Kingdom	Lung Cancer United States
Breast Cancer France	Oral Cancer India
Breast Cancer United Kingdom	Ovarian Cancer Australia
Chronic Lymphocytic Leukemia Spain	Ovarian Cancer United States
Colon Cancer United States	Pancreatic Cancer Australia
Gastric Cancer China	Pancreatic Cancer Canada
Leukemia United States	Pediatric Brain Tumors Germany
Liver Cancer France	Prostate Cancer Canada
Liver Cancer Japan	Rare Pancreatic Tumors Italy
	Renal Cancer European Union / France

and coordinated effort
cancer through the
ge-scale genome

TCGA Data Portal

[Access TCGA Data Portal](#)

[View the phase two list of targets to be sequenced in glioblastoma multiforme \(GBM\)](#)

TCGA: How Will It Work?

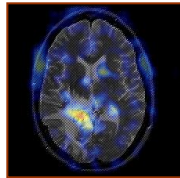
[Click here](#) for more information

Copy number, mutations, structural changes, expression, splicing, promoter methylation, miRNAs, protein levels

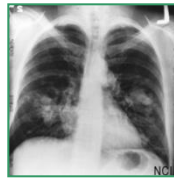
TCGA: A comprehensive approach to aberrant pathway definition

25 forms of cancer

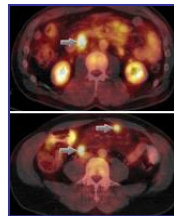
glioblastoma multiforme
(brain)



squamous carcinoma
(lung)



serous
cystadenocarcinoma
(ovarian)



Etc. Etc. Etc.

Biospecimen Core
Resource with more
than 150 Tissue Source
Sites

6 Cancer Genomic
Characterization
Centers

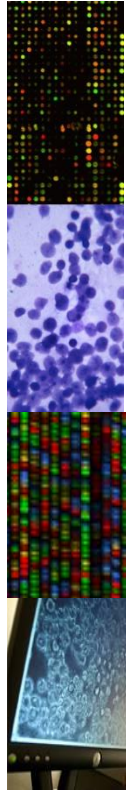
3 Genome
Sequencing
Centers

7 Genome Data
Analysis Centers

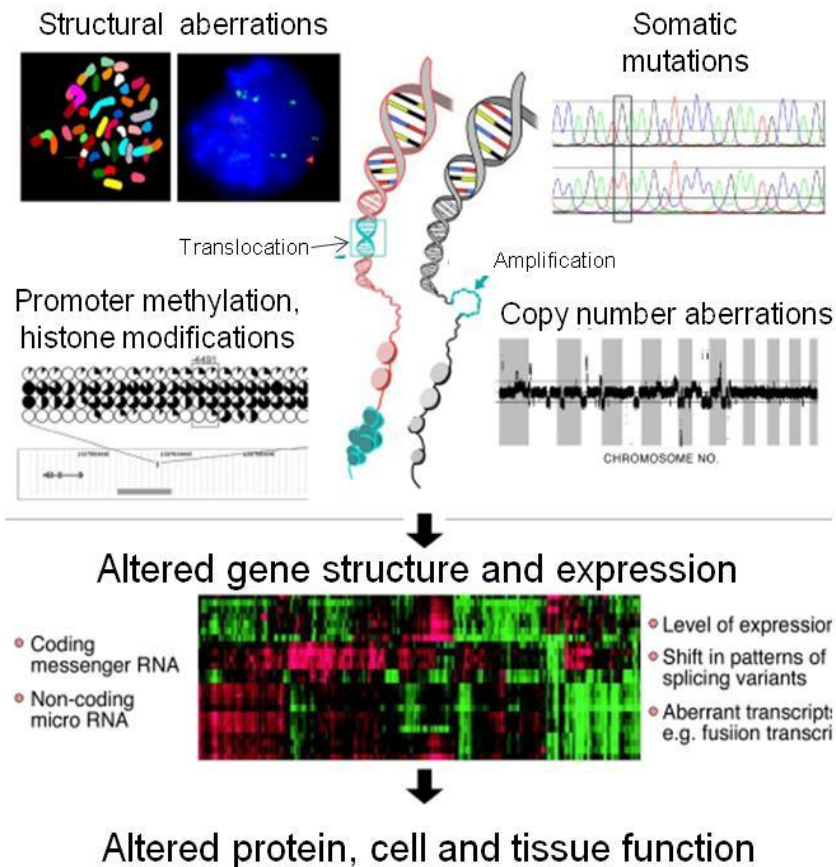
Data Coordinating
Center

Multiple data types

- Clinical diagnosis
- Treatment history
- Histologic diagnosis
- Pathologic report/images
- Tissue anatomic site
- Surgical history
- Gene expression/RNA sequence
- Chromosomal copy number
- Loss of heterozygosity
- Methylation patterns
- miRNA expression
- DNA sequence
- RPPA (protein)
- Subset for Mass Spec

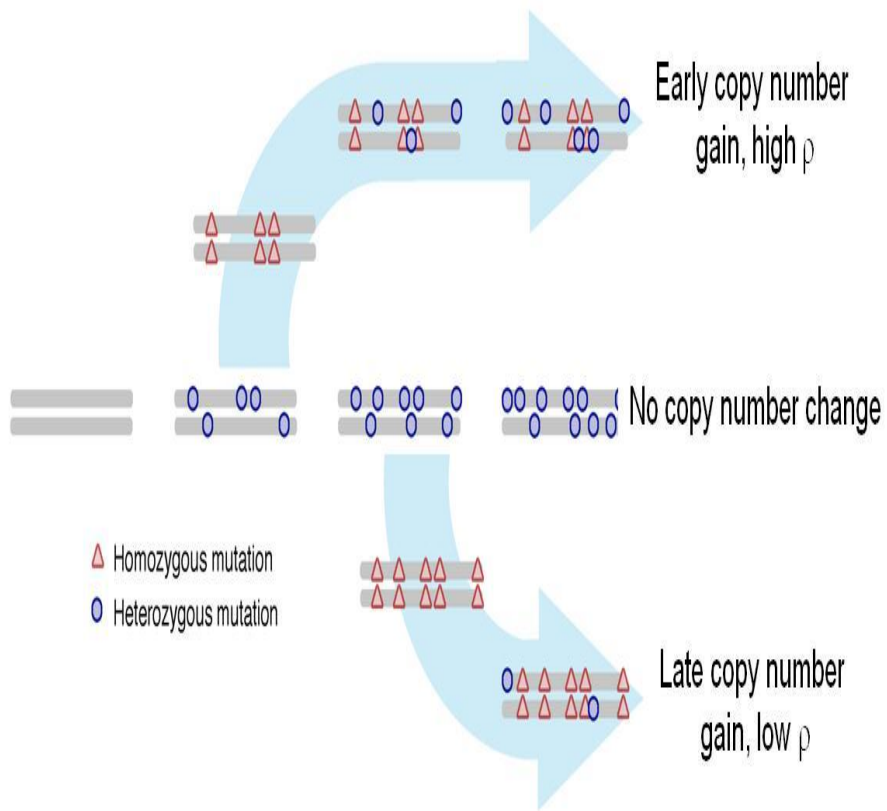


State of the cancer genome



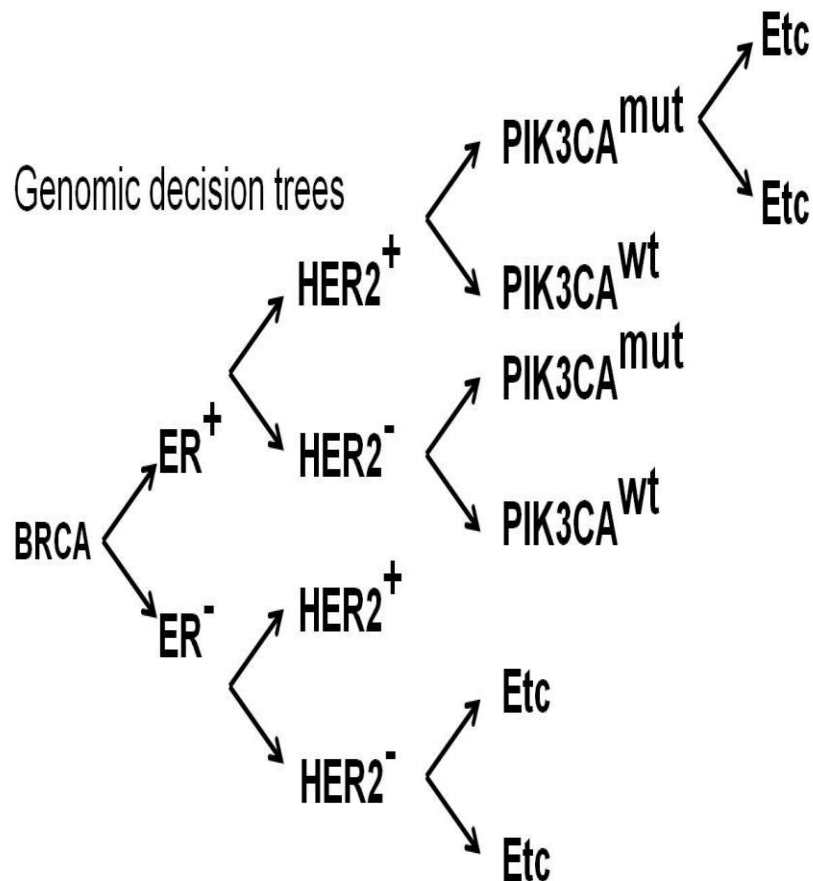
- Multiple genomic mechanisms deregulate genes that contribute to cancer pathophysiology
- Some aberrations occur earlier than others and can be ordered using information from one sample
- Recurrent aberration patterns define breast cancer subtypes that differ in outcome and therapeutic response

State of the cancer genome



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State of the cancer genome



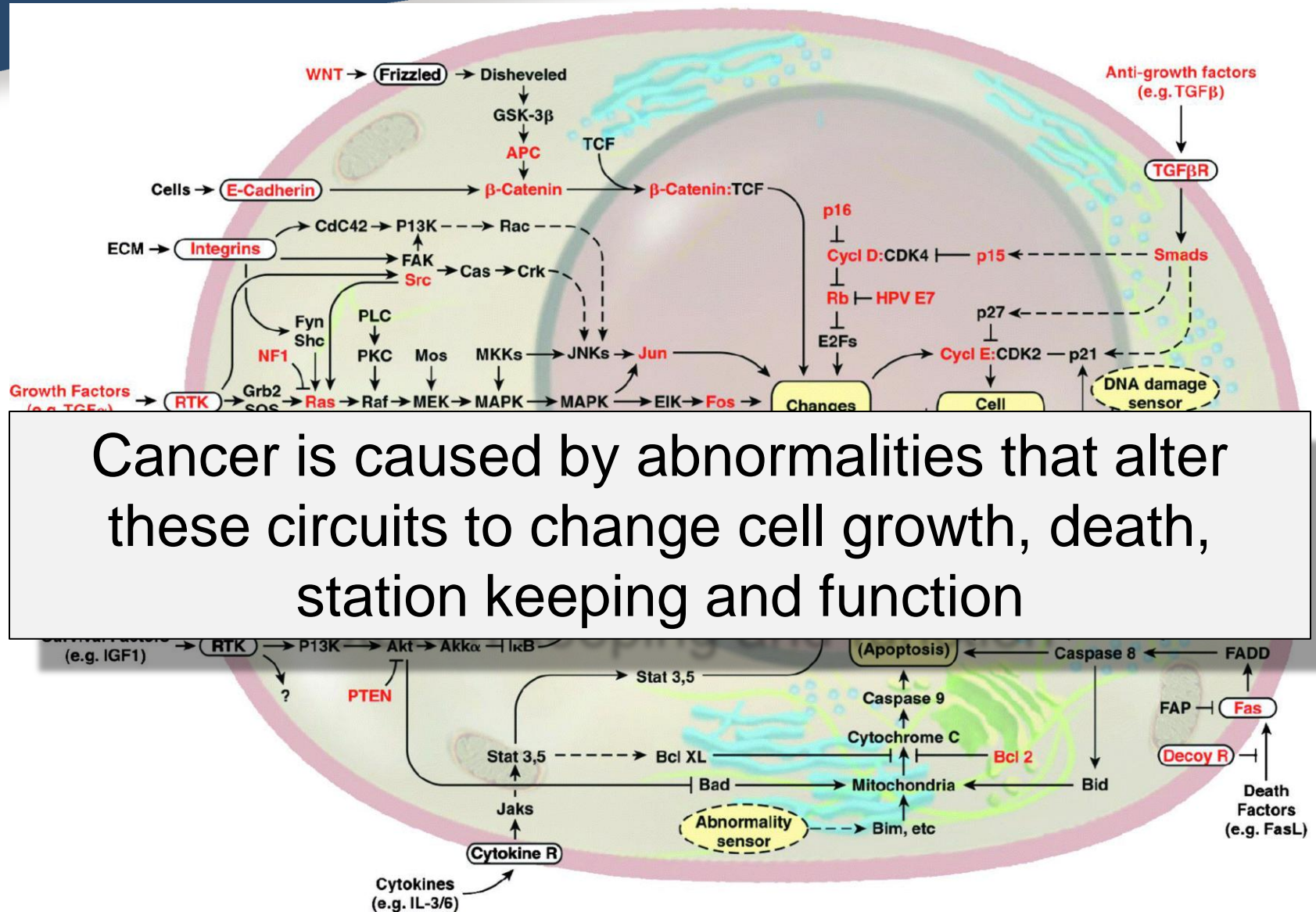
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Omics and beyond

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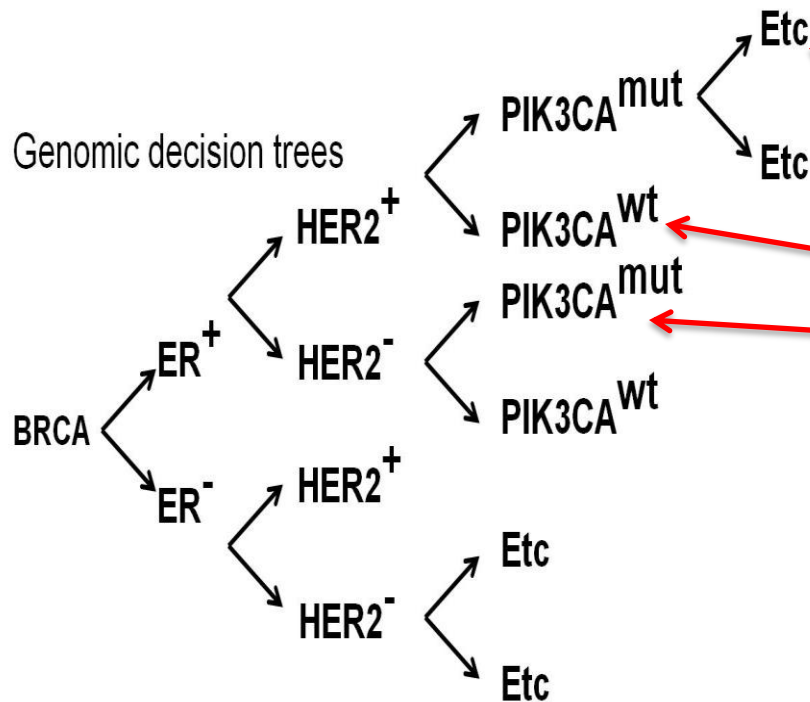
Genomic aberrations deregulate cellular regulatory systems



Cancer is caused by abnormalities that alter these circuits to change cell growth, death, station keeping and function

Therapeutic approaches either attempt to restore proper regulation or inhibit growth of deregulated cells

>\$100 Billion in drug development



Almost 100 anticancer drugs now have FDA approval

DRUG NAME	DRUG NAME	DRUG NAME	DRUG NAME	DRUG NAME	DRUG NAME
Imiquimod	Allopurinol	Sunitinib	Vincristine sulfate	Mifexentrone	Gefitinib
Erlotinib HCl	Busulfan	Mitoxentrone	Vincristine sulfate	Gefitinib	Thiotepa
Tolengronic acid	Thalidomide	Gefitinib	Bleomycin	Dasatinib	Ureacil mustard
Amifostine	Pentostatin	Dasatinib	Paclitaxel	Imatinib	Tretinoin
Melphalan	Temozolamide	Imatinib	Velirubin	Sorafenib	Deunorubicin HCl
Azathioprine	Rapamycin	Sorafenib	Nilotinib	Relaxifene HCl	Topotecan HCl
Decitabine	Fulvestrant	Sorafenib HCl	Yezobepilone	Doxorubicin HCl	Docarbazine

2009 Report
Medicines in Development for Cancer
 PRESENTED BY AMERICA'S PHARMACEUTICAL RESEARCH COMPANIES

More Than 800 Medicines and Vaccines in Testing Offer Hope in the Fight Against Cancer

Few things cause patients more fear and uncertainty than a cancer diagnosis. But today—because of a steady stream of new and improved medicines and treatments—cancer increasingly can be managed and even beaten. President Obama has called for a cancer cure in our lifetime, patients and their families are looking for more and better treatments, and America's pharmaceutical research and biotechnology companies are responding.

Pharmaceutical researchers are now working on 861 medicines for cancer. Many are high-tech weapons to fight the disease, while some involve innovative research on using existing medicines in new ways.

The medicines in development—all in either clinical trials or under Food and Drug Administration review—include 122 for lung cancer, the leading cause of cancer death in the United States; 106 for breast cancer, which is expected to strike more than 180,000 American women each year; 103 for prostate cancer, which is expected to

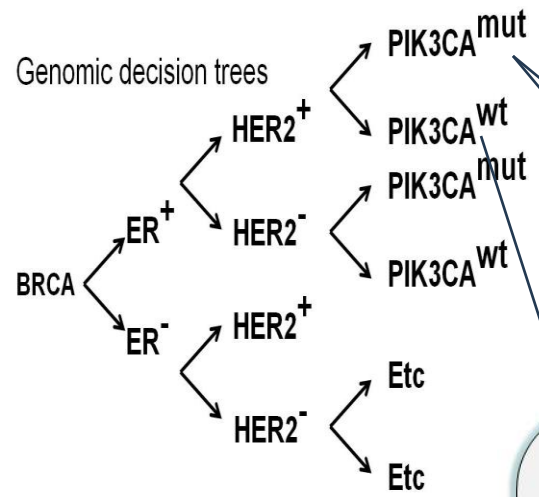
Cancer Type	Number of Medicines
Bladder Cancer	31
Breast Cancer	106
Brain Cancer	61
Cervical Cancer	11
Colonial Cancer	70
Head/Neck Cancer	34
Kidney Cancer	44
Leukemia	129
Liver Cancer	15
Lung Cancer	122
Lymphoma	96
Multiple Myeloma	32
Ovarian Cancer	41
Pancreatic Cancer	54
Prostate Cancer	103
Sarcoma	27
Skull Cancer	47
Solid Tumor	203
Stomach Cancer	29
Cancer/Related Conditions	31
Other Cancers	53
Unspecified Cancers	74

*Some medicines are listed in more than one category.

• A potential first-line treatment (meaning it's given to patients before any other treatment) and first-in-class medicine, designed to target specific cancer cells and...

Modeling the decision tree – panels of cell lines that capture the important aberration combinations

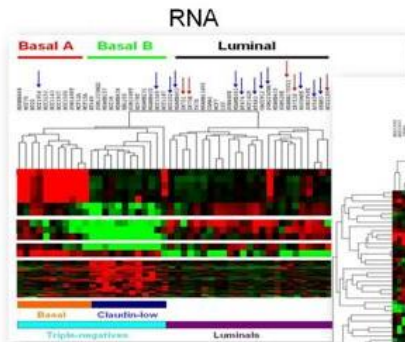
Our goal is to include multiple cell lines in the panel that model each important decision state



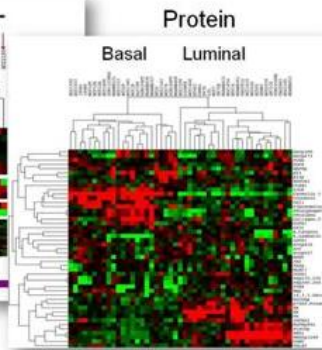
Breast cancer cell lines

184A1	HCC1143BL	HCC2218	MDAMB157	SUM1315MO2	ZR7530
184B5	HCC1187	HCC3153	MDAMB175VII	SUM149PT	ZR75B
600MPE	HCC1395	HCC38	MDAMB231	SUM159PT	
AU565	HCC1419	HCC38BL	MDAMB361	SUM185PE	
BT20	HCC1428	HCC70	MDAMB415	SUM190PT	
BT474	HCC1500	HS578T	MDAMB435	SUM225CWN	
BT483	HCC1569	LY2	MDAMB436	SUM229PE	
BT549	HCC1599	M4A4	MDAMB453	SUM44PE	
CAMA1	HCC1806	MB157	MDAMB468	SUM52PE	
DU4475	HCC1937	MCF10A	MX1	T47D	
HBL100	HCC1954	MCF10F	NM2C5	T47D_KBluc	
HCC1007	HCC202	MCF12A	S1	UACC812	
HCC1008	HCC2157	MCF7	SKBR3	UACC893	
HCC1143	HCC2185	MDAMB134VI	SUM102PT	ZR751	

This works only to the extent that the cell lines capture the genomic events that determine response in tumors

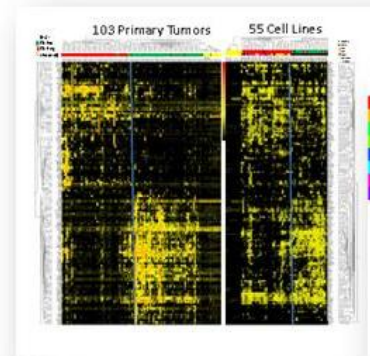


Spellman, Sadananadam



Mills, Lu

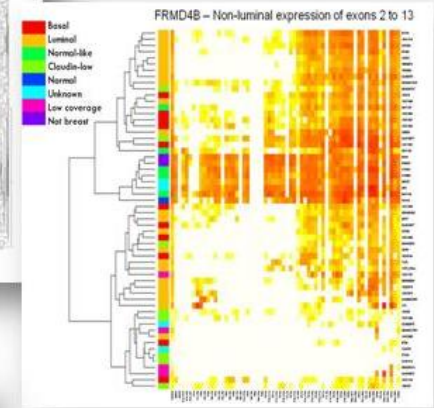
Promoter methylation



Genome copy number

Sukumar

Alternative splicing



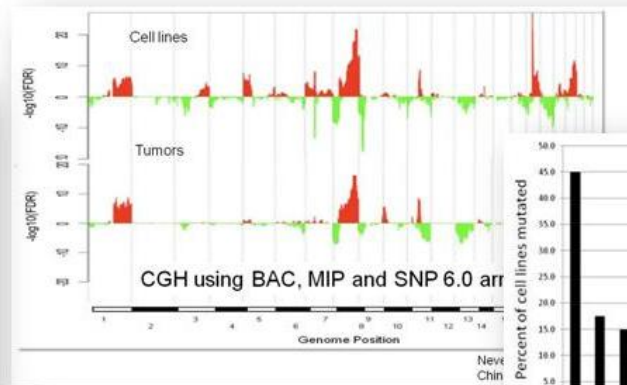
Griffith, Daeman

Fusion transcripts

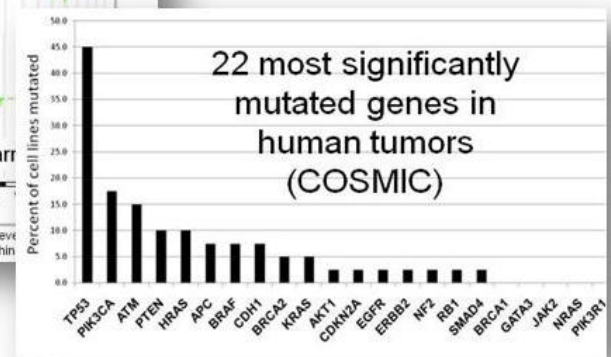
Cell lines	Number of fusion genes	Cell lines	Number of fusion genes
600MPE	8	HCC153	16
BT20	21	HCC70	17
BT474	5	LY2	8
BT483	1	MCF7	5
BT459	17	MDAMB134V	14
HCC1143	0	MDAMB361	34
HCC1149	7	MDAMB453	17
HCC1428	18	SKBR3	13
HCC1500	19	SUM149PT	1
HCC1569	24		
HCC1599	14		
HCC1806	18		
HCC1937	9		
HCC1954	33		
HCC202	3		
HCC2218	10		

332 total fusions
5.3/line average
ERBB2, GRB7, SMAD2 recurrent

Sadanadam



Mutations



Pepin, Durinck

The cancer genome browser

genome-cancer.ucsc.edu

The screenshot shows the Cancer Genomics Browser interface. At the top, there are navigation links for 'Home', 'Browser', and 'Help'. The main header includes 'Tumor Images', 'Genome Browser', and a user profile 'Hello JingchunZhu.' with 'My account' and 'Sign out' options. The title 'Cancer Genomics Browser' is on the right. Below the header, there are tabs for 'Datasets', 'Genesets', and 'Signatures'. A search bar contains 'chr1-chr22' and shows '2,867,732,772 bp'. There are buttons for 'View in Genome Browser' and 'RefSeq Genes'. On the left, a list of datasets is visible, with 'Stand Up To Cancer (standardized clinical)' highlighted in a red box. The main content area displays three tracks: 'Breast Cell Line SNP Segmented (Gray Lab) • N=53', 'Breast Cell Line Exon Expression (Gray Lab) • N=55', and 'Breast Cell Line HumanMethylation27 DNA Methylation (Gray Lab) • N=50'. Each track has a 'Features' panel on the right. Annotations include: 'select dataset to view' pointing to the dataset list; 'configure genesets', 'configure genomic signatures', and 'link to human genome browser' pointing to the top navigation; 'resize panels' pointing to the track headers; 'view in chromosome mode' and 'view in gene mode' pointing to track view options; 'position or gene search bar' pointing to the search bar; 'toggle on/off RefSeq genes' pointing to the 'RefSeq Genes' button; and 'Facilitates association between genotype and phenotype' pointing to the tracks. A red arrow points from the 'Stand Up To Cancer' dataset to the tracks.

Facilitates association between genotype and phenotype

SU2C project data

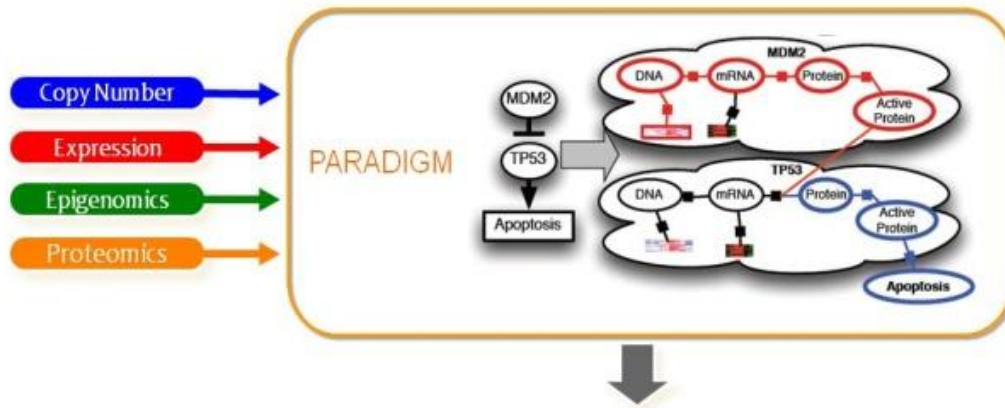
- User signon required
- Side by side with public-tier, TCGA, ISPY datasets
- New browser release Jan 23, 2012

Understanding target pathways

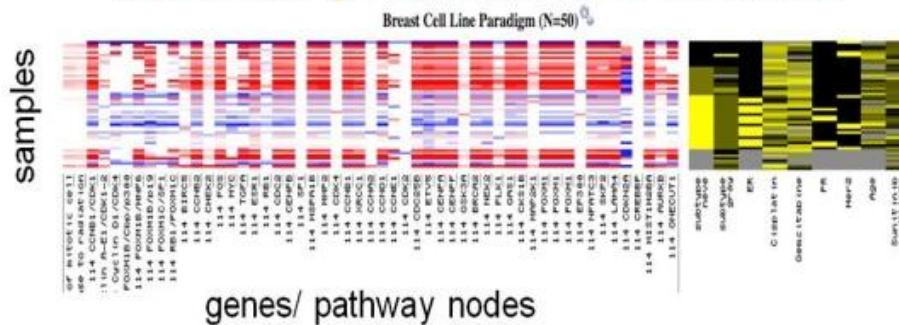
Cancer Genome Browser
PARADIGM activities

Stuart/Haussler et al

Informatics consortium



PARADIGM Integrated Activities in Cancer Browser



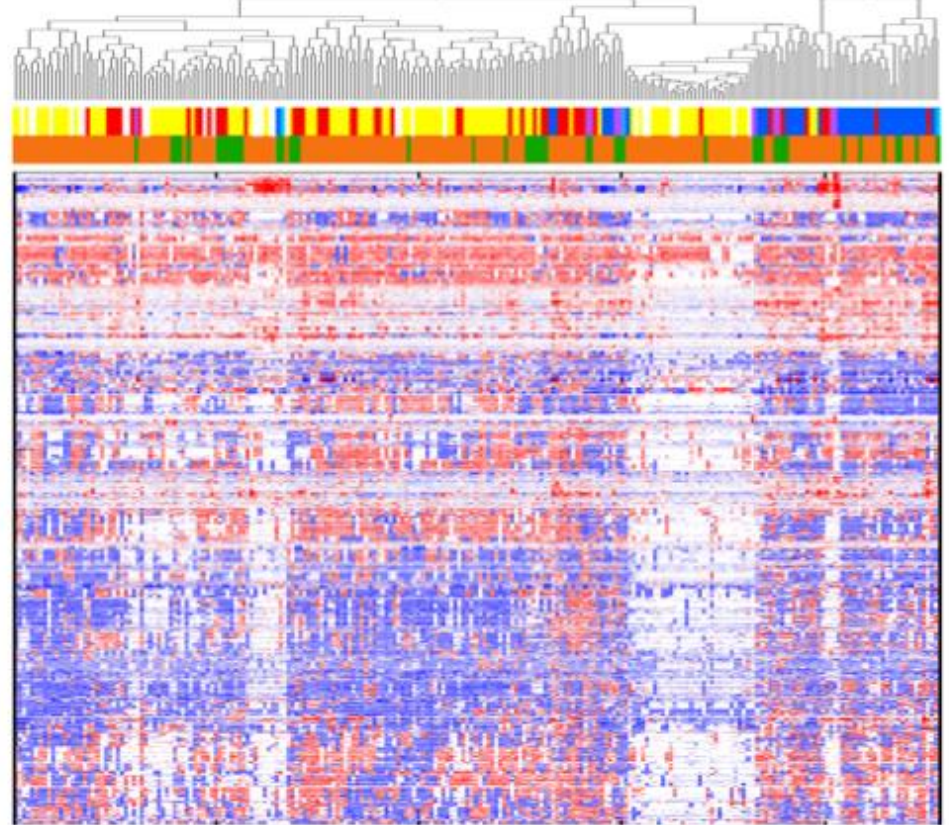
SU2C

Using PARADIGM to assess subtype specific pathway

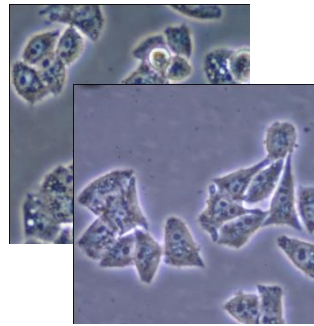
Activities for 1441 pathways

- Tumors and cell lines show common pathway signatures
- Pathway activities show strong subtype specificity

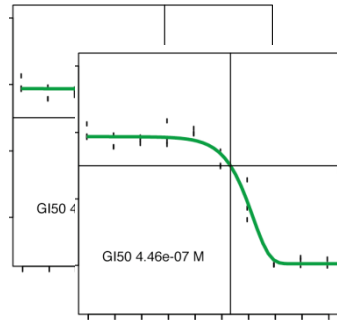
TCGA tumors and breast cancer cell lines



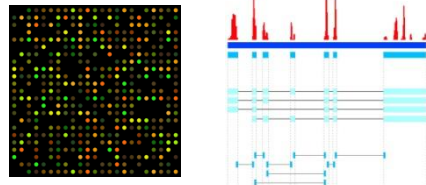
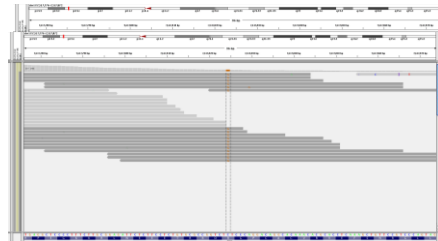
Predictive markers are discovered by correlating the “ome” with quantitative response



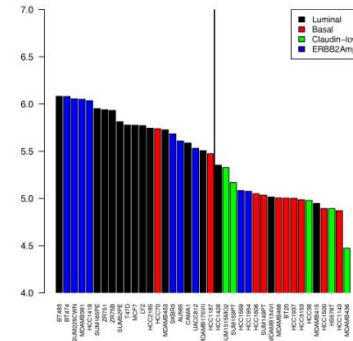
Breast cancer cell line collection



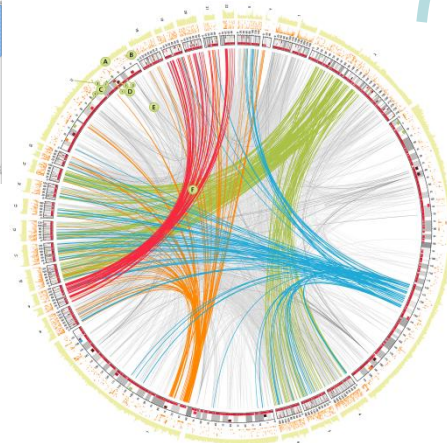
Drug/siRNA response



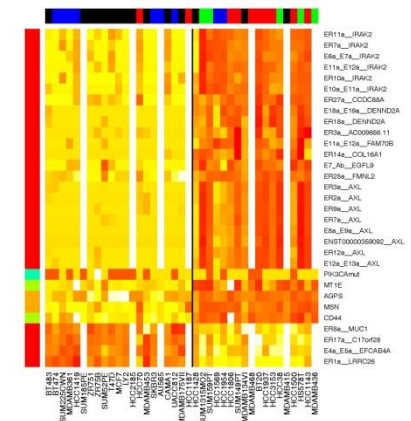
Molecular data: 9+ data types



Response status

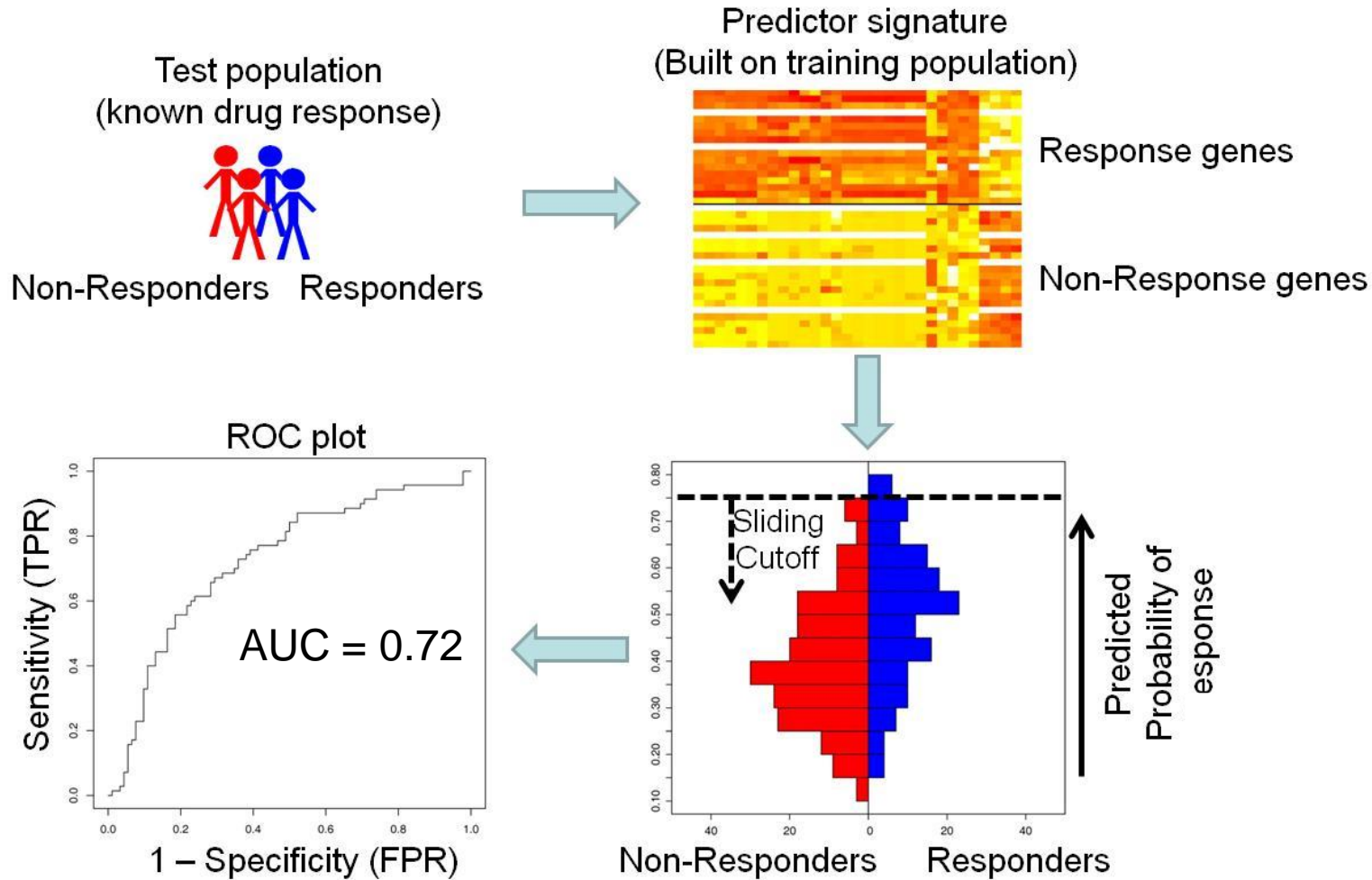


- Tested >140 therapeutic compounds in 54 cell lines
- Treat for 72 hours
- Test 9 drug doses: low to high
- 3 replicates
- GI50: Drug dose required to inhibit growth by 50%



Molecular drug response signatures

Machine learning approaches (random forests) identify quantitative predictive decision trees



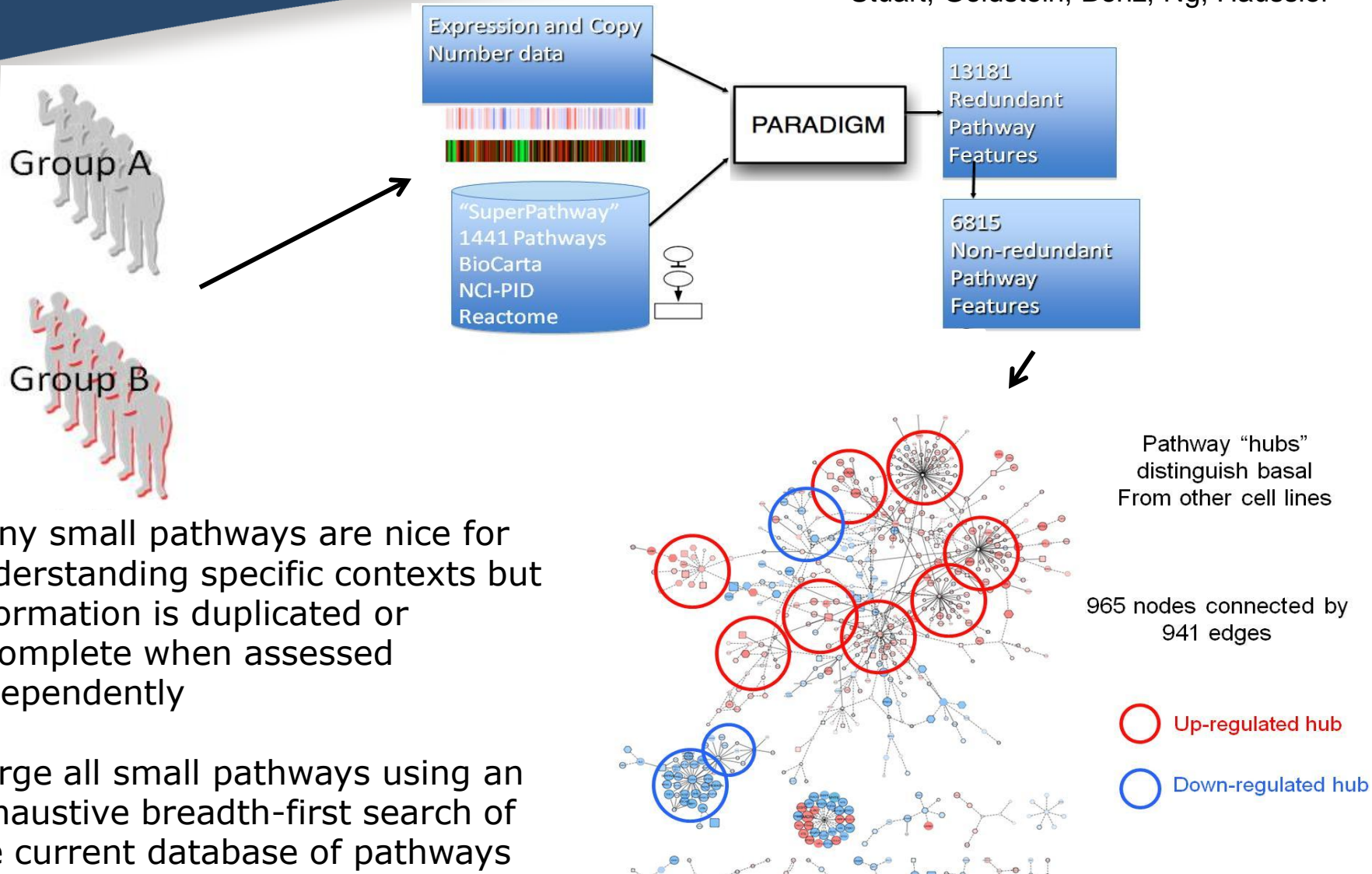
Anneleen
Daemen



Obi
Griffith

“Superpathways” – generating information on mechanisms of response

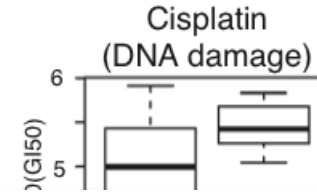
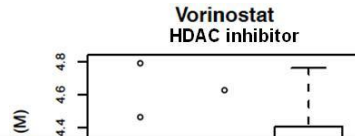
Stuart, Goldstein, Benz, Ng, Haussler



This approach identified pathway subnetworks associated with compound response



Lau
Heis

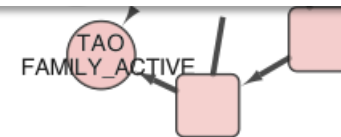


We are now applying the siRNA knockdown to validate the predicted networks

Goal: Predict molecular and phenotype response for each gene in the network and test via siRNA knockdown

Compounds attacking validated subnetworks are candidate therapeutics

Histone deacetylase network



DNA repair network

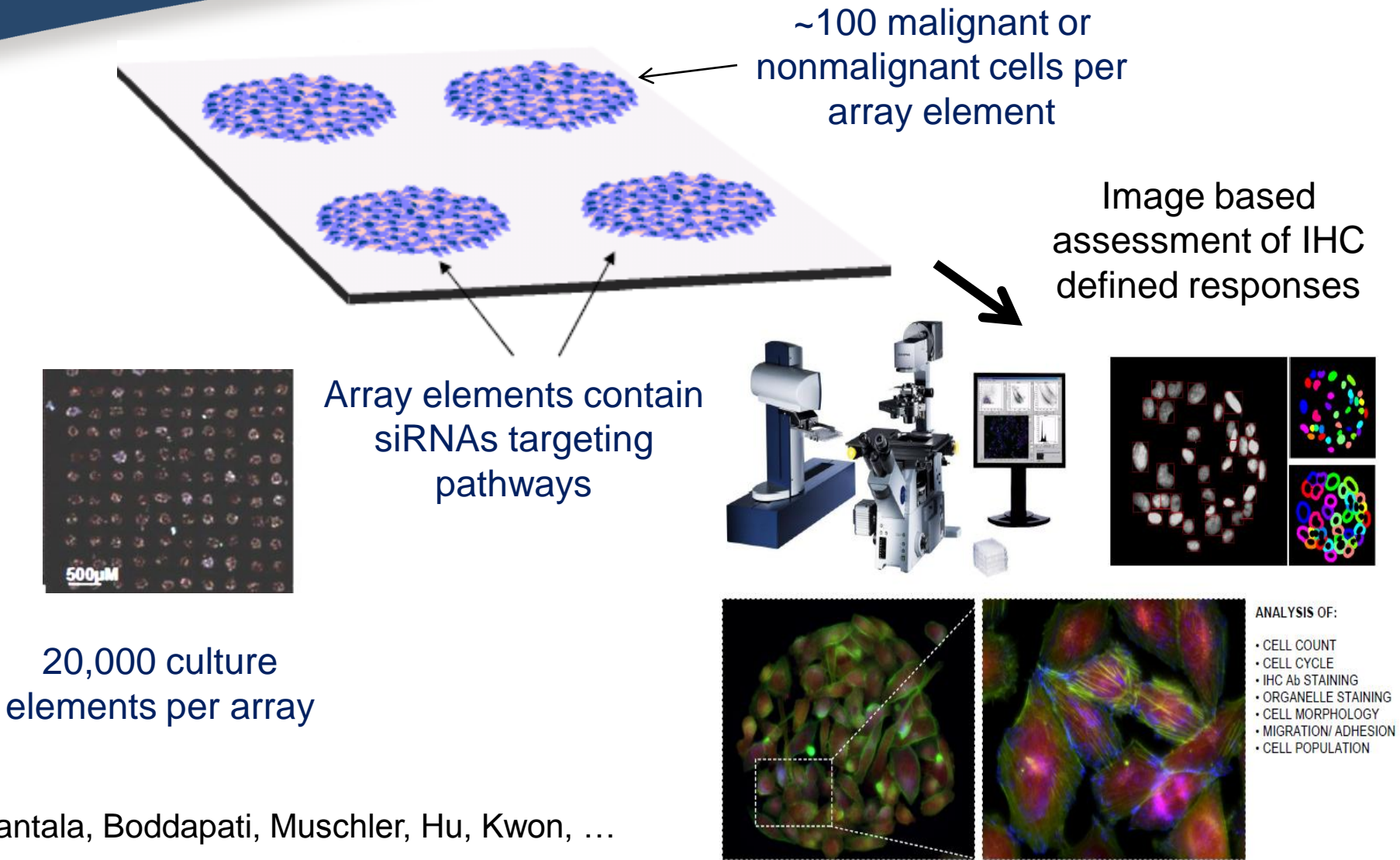
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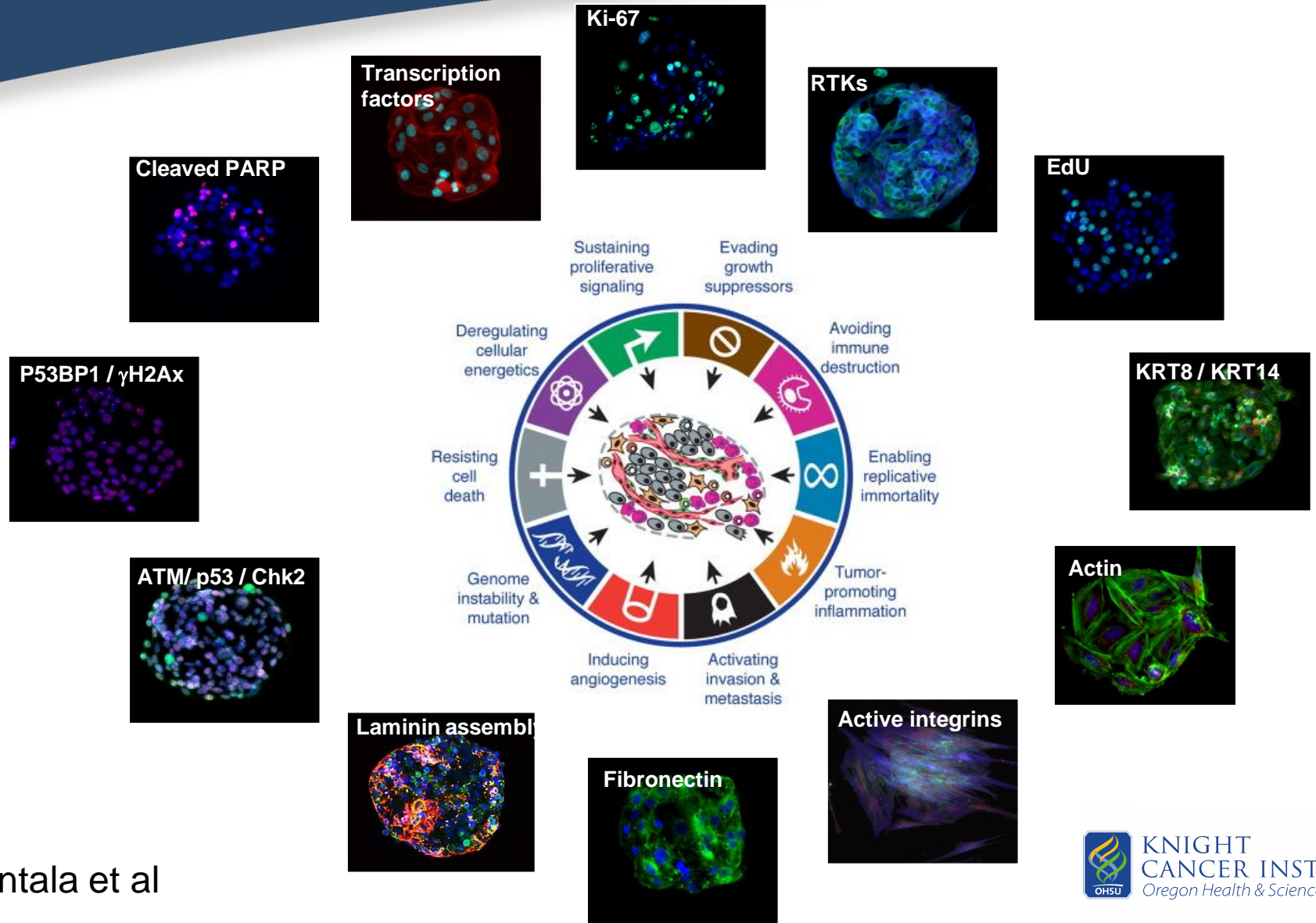
Compounds attacking validated subnetworks are candidate therapeutics

Validating “driver” pathways that affect specific cancer hallmarks



Rantala, Boddapati, Muschler, Hu, Kwon, ...

Imaging assays for cancer hallmarks

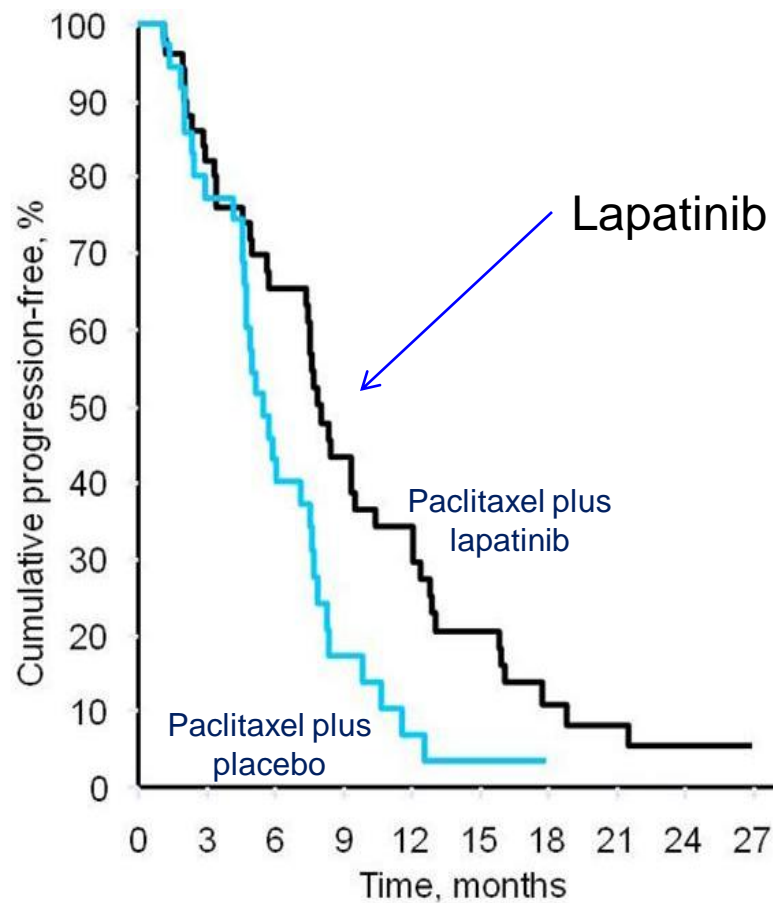


Omics and beyond

Topics for discussion

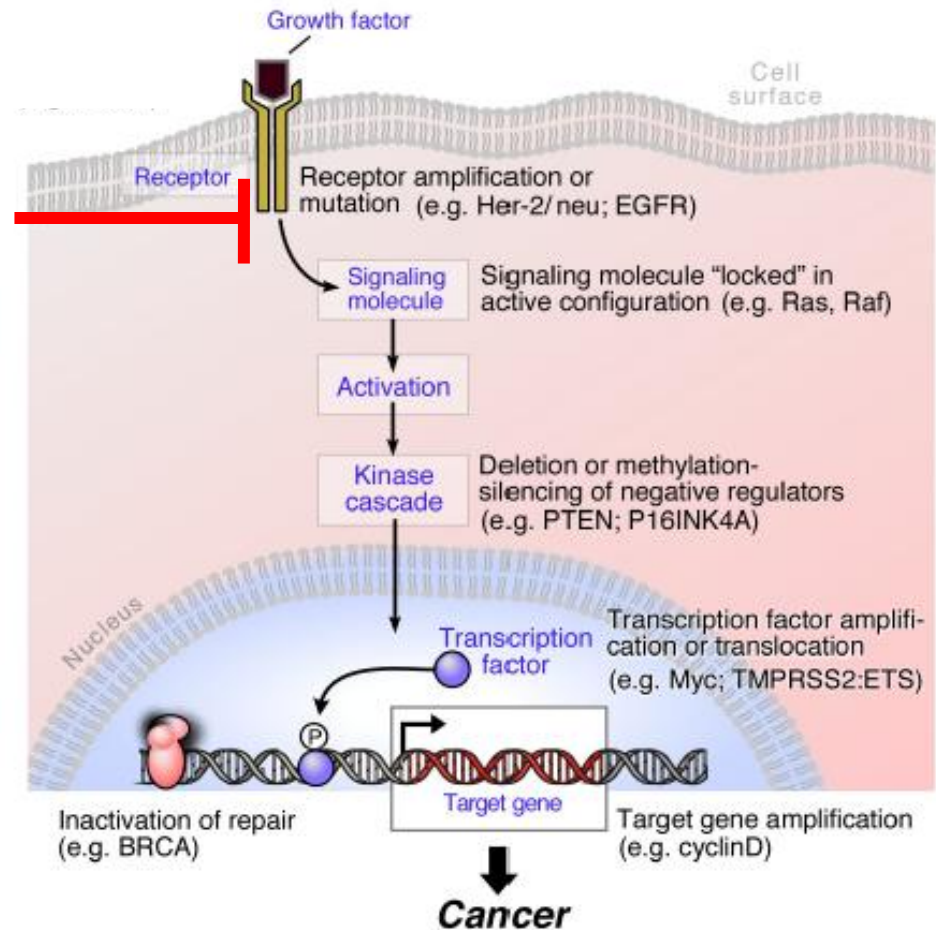
- The state of the cancer “ome”
- Developing a molecular basis for therapeutic response
- **Beyond genomics – understanding the micro- and nanoenvironments**

Genome aberration targeted therapies are not as durable as needed



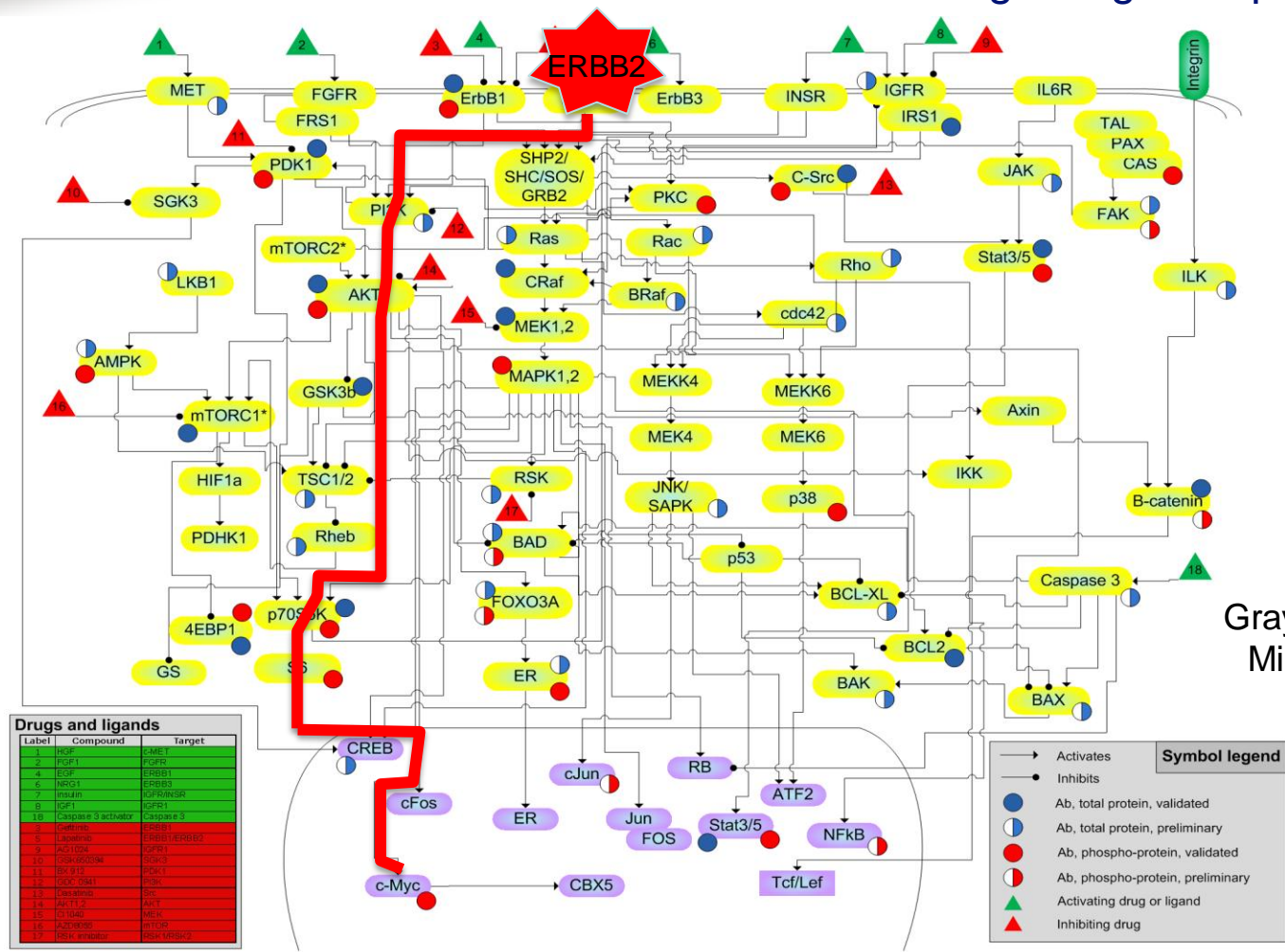
Di Leo et al., ASCO 2007

Understanding the micro- and nano-environments of cancer



Development of strategies to target pathways deregulated by genome aberrations is a key goal

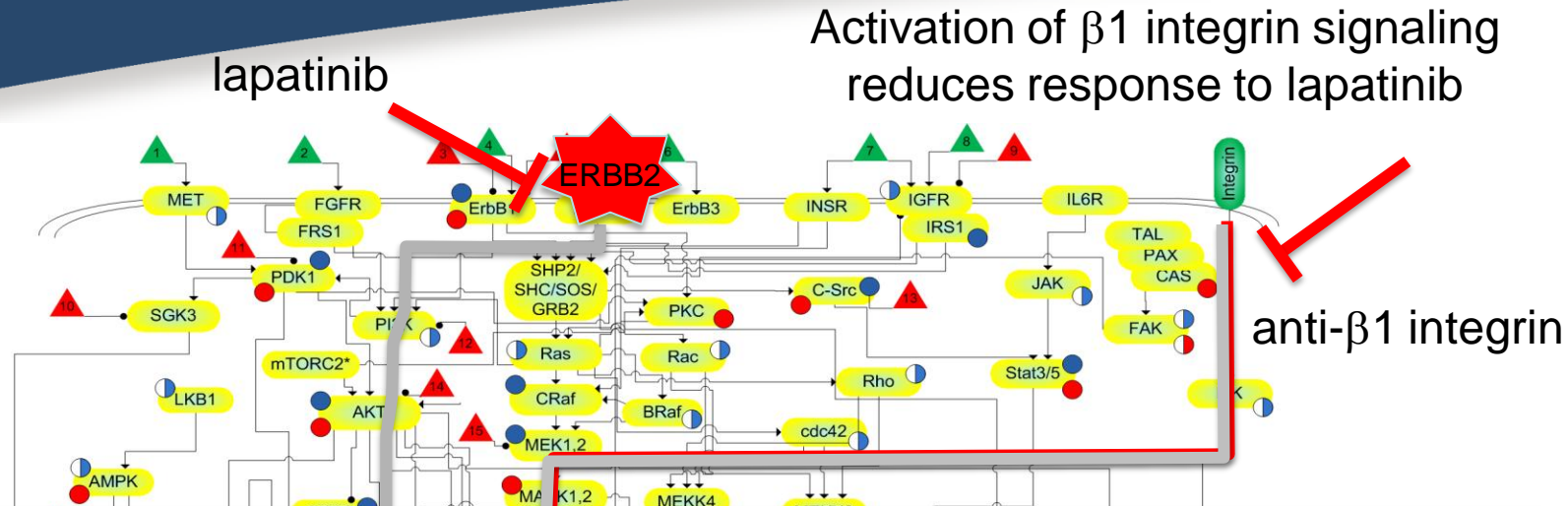
Understanding the larger signaling enterprise



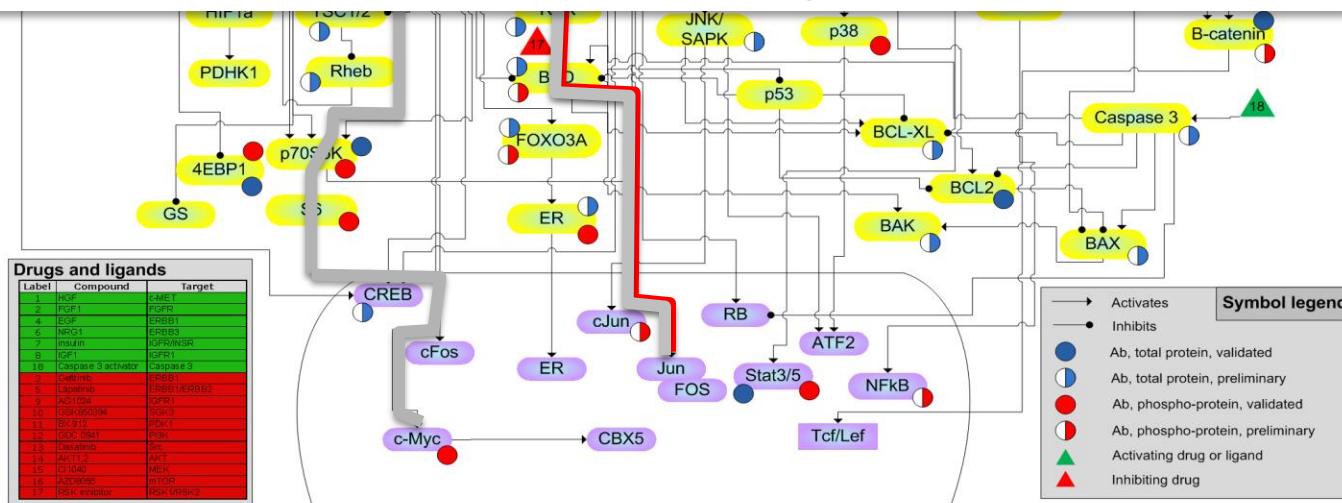
Gray, Spellman, Mills, Tomlin, Korn



Microenvironment signaling can bypass inhibitors



Are there other microenvironment signals that alter response?



Modeling the microenvironment

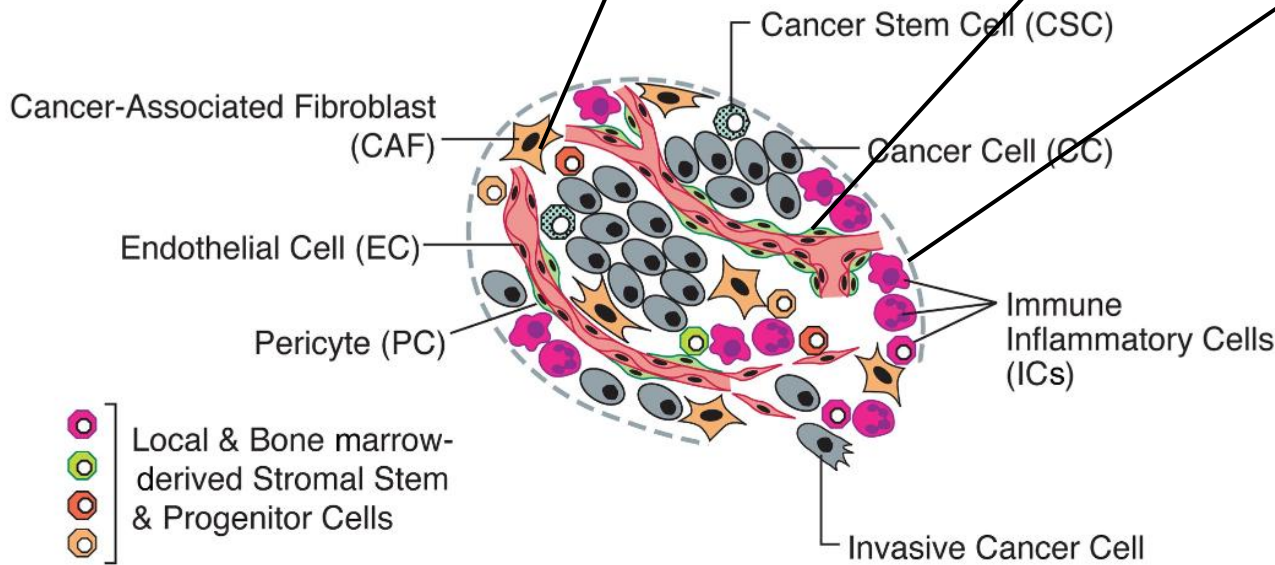
Microenvironment microarrays

Korkola, LaBarge, Rantala

Cancer and normal cells

Arrays of microenvironment proteins

Up to 20,000 per analysis



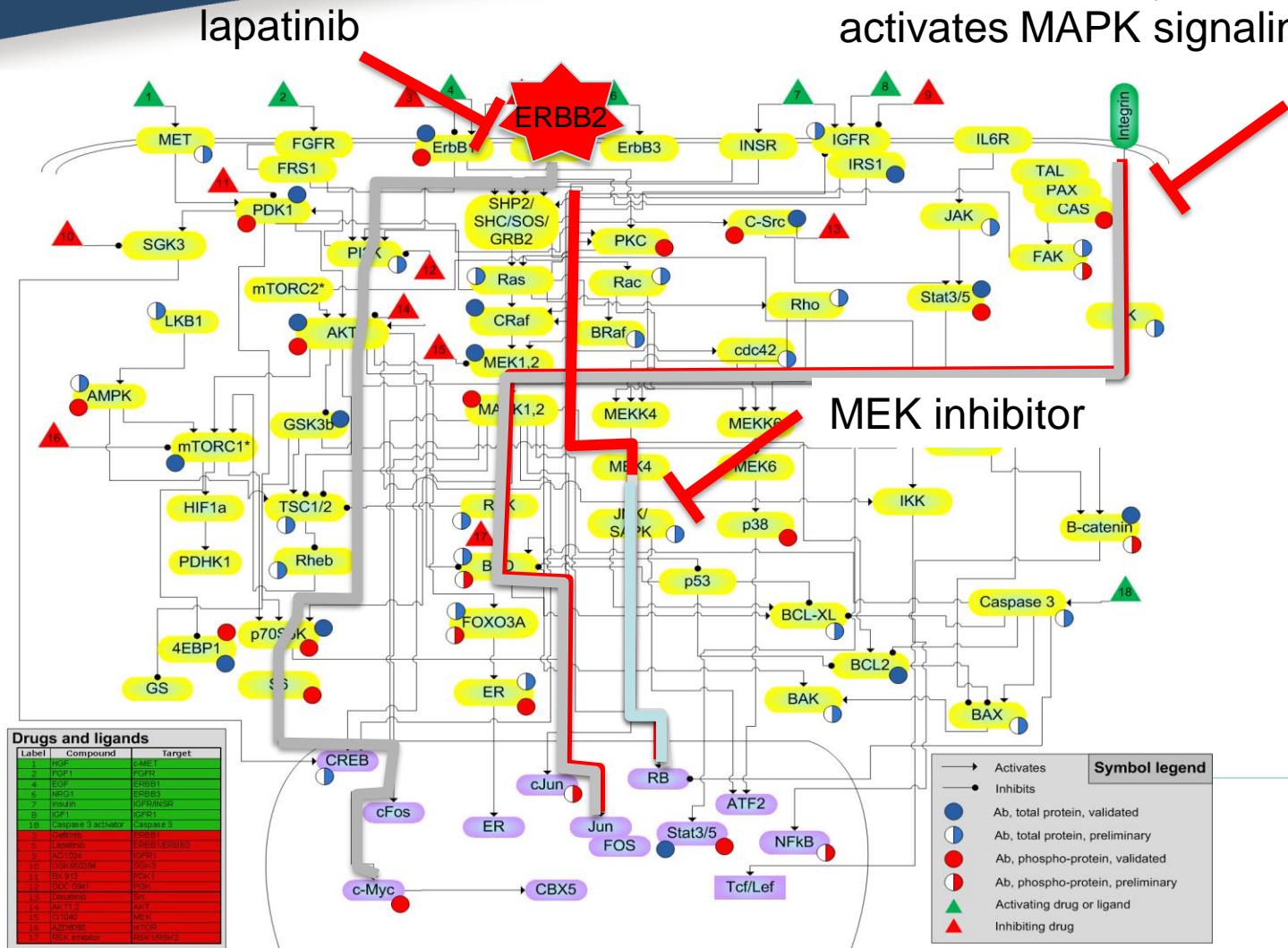
Predicting responses to cancer therapies

Topics for discussion

- Linking genes/pathways to therapeutic response
- Understanding the role of the microenvironment
- Visualizing the nanoenvironment – exploring the mechanics of signaling

Activation of bypass pathways

Release of inhibitory cross-talk activates MAPK signaling



Activation of bypass pathways

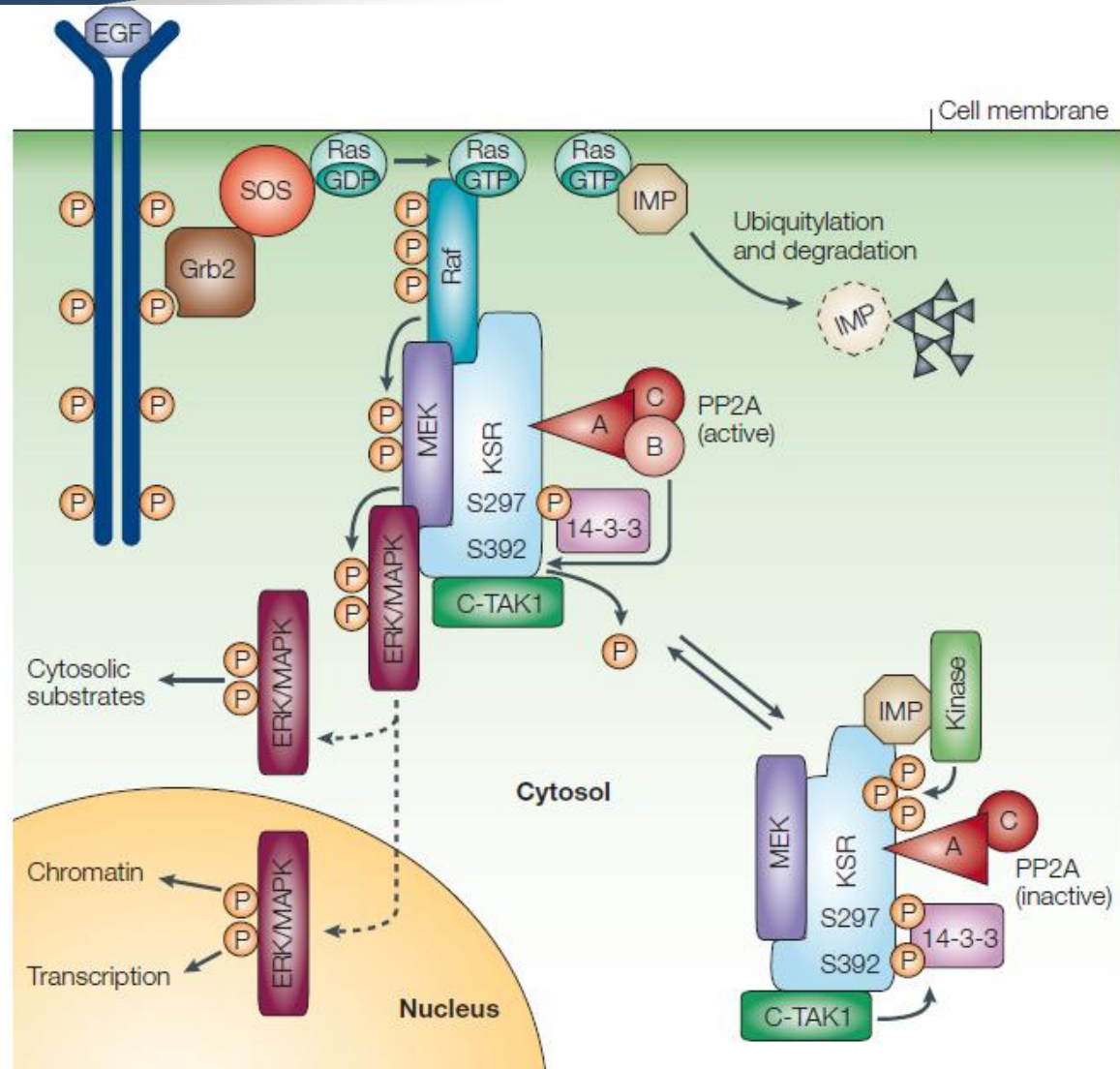
Combinatorial Rx becomes increasingly toxic unless targeting is very precise

How does all of this information get integrated?

We don't know where or how it gets translated into action (proliferation, death, etc)

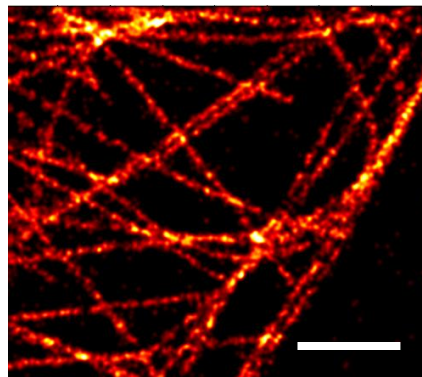
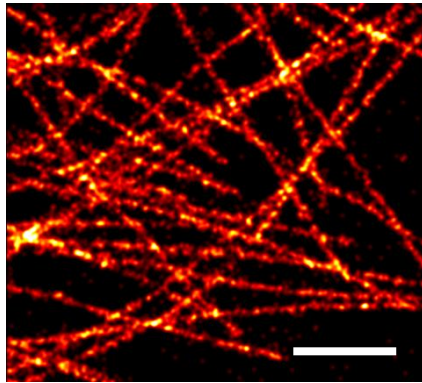
Goal – visualizing the signaling architecture

An approach to assessment of digital signal transport

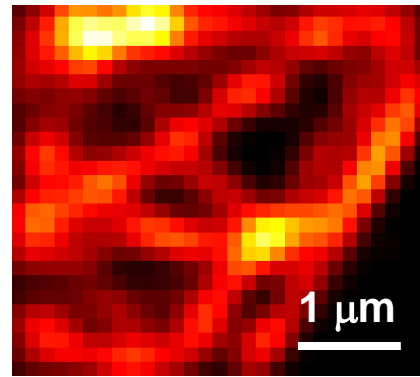
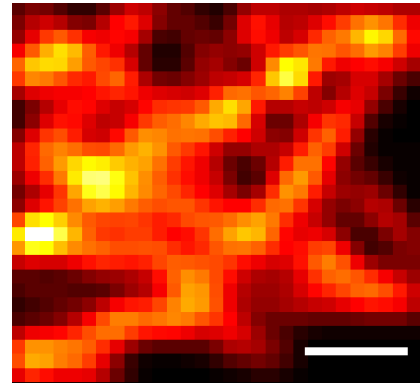


Advances in imaging, chemistry and computational Analysis can allow these structures to be seen

Super resolution



Conventional



Fluorescence imaging at nanometer resolution

Super resolution fluorescence microscopy to the rescue

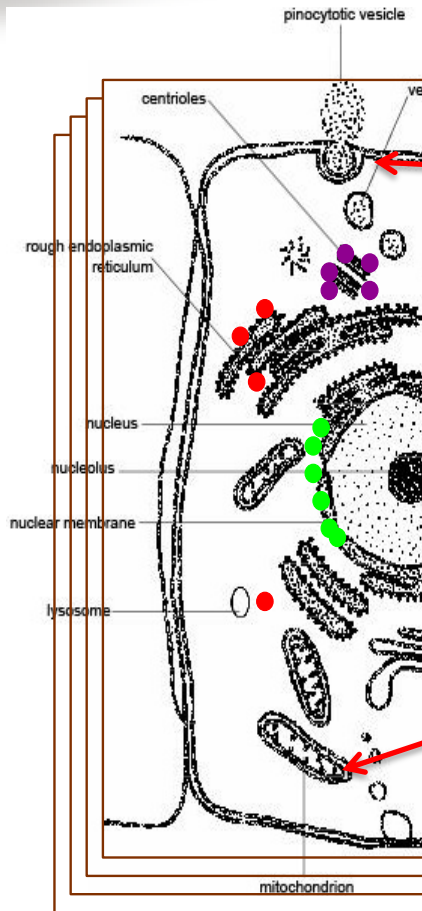
Super resolution imaging concept

- The average X, Y location of a fluorescent molecule can be determined with few nanometer accuracy
- The locations of two closely spaced fluorescent molecules can be mapped with this precision as long as only one is on at a time
- Super resolution images are built up over time by switching on a few dye molecules, recording their positions, switching them off and doing a few more

Better imaging through chemistry

Identifying signal action centers

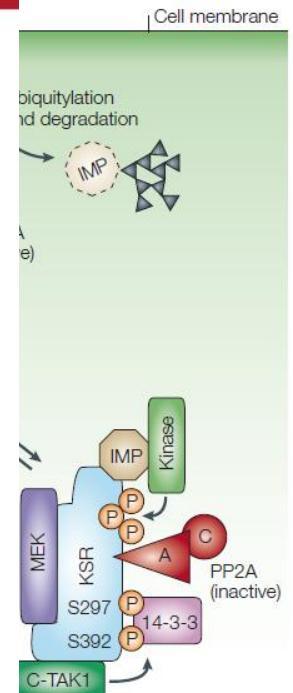
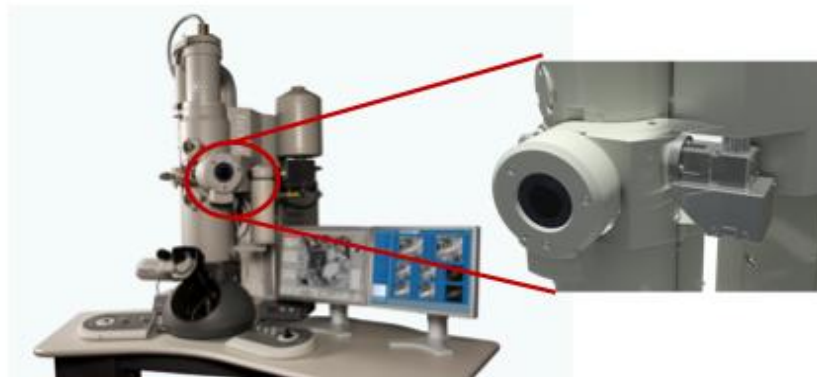
Localization of signaling structures defined using FM
on cellular action centers defined using EM



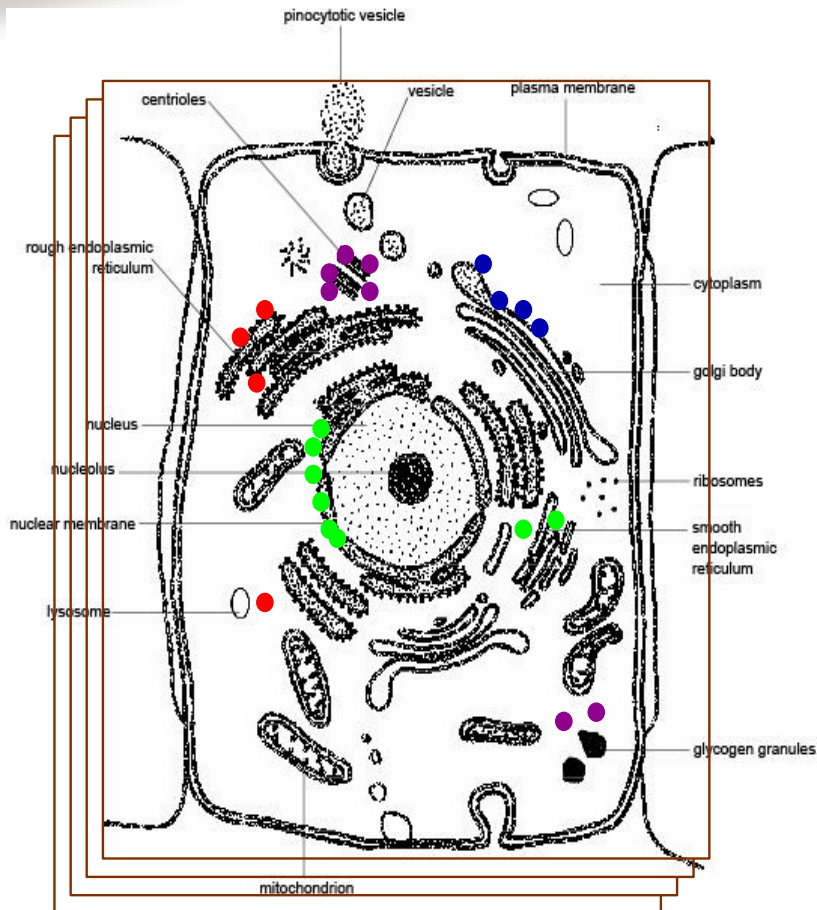
Tecnai iLEM™

Tecnai iLEM™

The Integrated Light and Electron Microscope;
a fast, accurate, and automated solution for
correlative light and electron microscopy.



Modeling Paradigm: Encoding the State Space



Targets

- ERK/MAPK
- MEK
- RAF
- KSR



Structures

- Cell Membrane
- Cytosol
- Nuclear Membrane
- Nucleus
- Golgi Body
- Endoplasmic Reticulum
- Lysosomes

E.g., State Value (● ERK/MAPK, Golgi Body) = 5

Model Space $|M| = O(|Targets| \times |Structures|)$

Cancer genomics and imaging

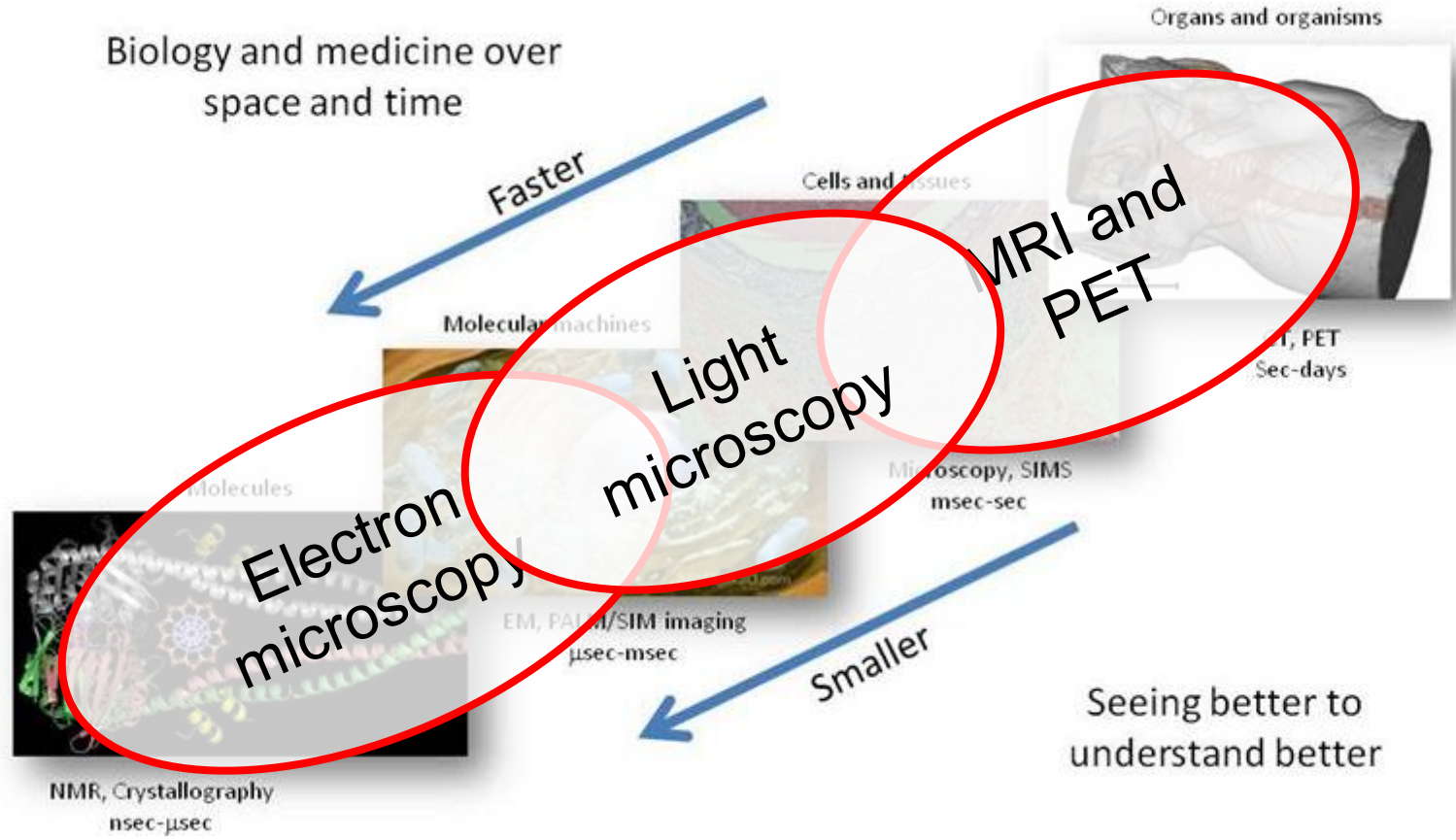
Aberration catalog will soon be completed for most major cancer types

High throughput, high content imaging strategies can define the impact of microenvironments on response

Imaging the micro- and nano-environments will facilitate development of more robust and precisely targeted therapies

Research pursued under the auspices of the OHSU Center for Spatial Systems Biomedicine

Integrating engineering, imaging, biology, chemistry and computer science to advance multiscale imaging science



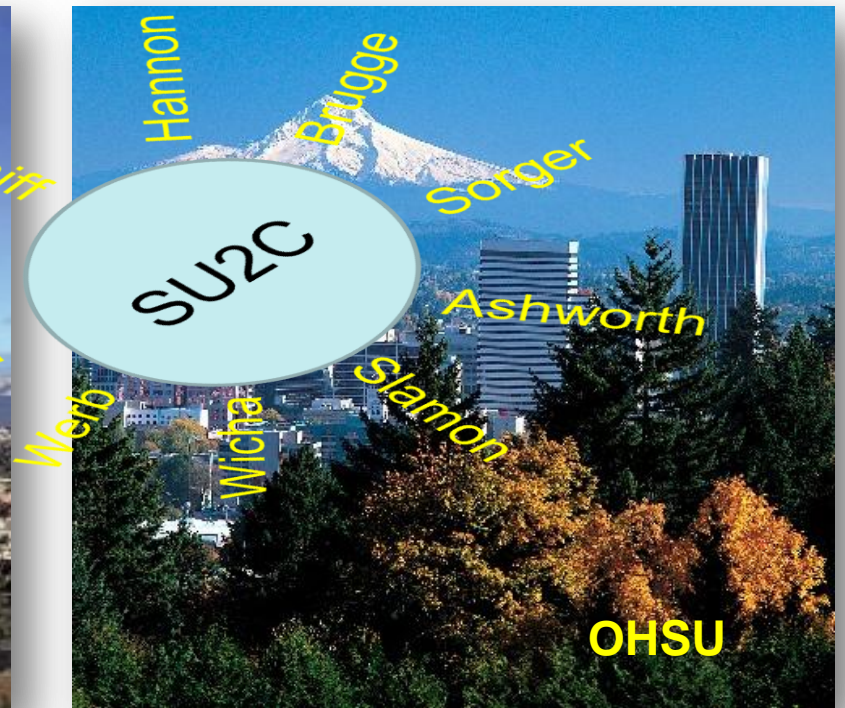
Omics and beyond

The collaborative village

SPORE, TCGA, DOD, PSOC, CPTAC, ICBP, I SPY



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